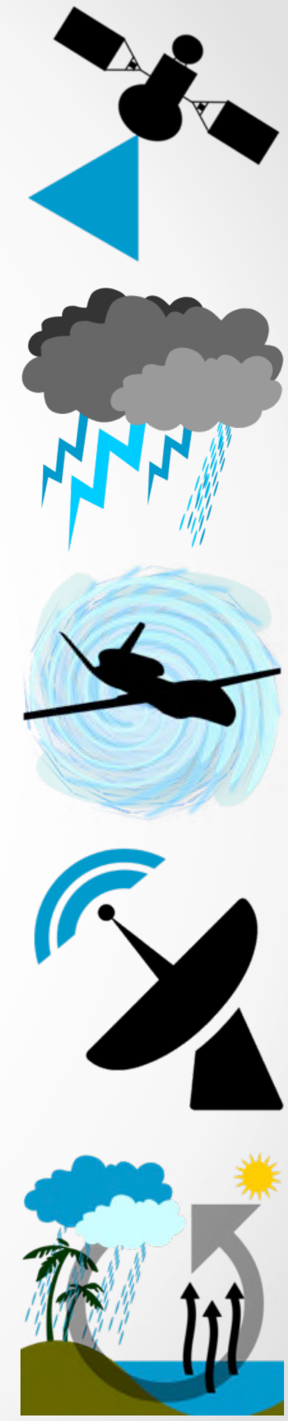
EXPLOITING UNTAPPED INFORMATION RESOURCES IN EARTH SCIENCE

Rahul Ramachandran NASA/MSFC, **Peter Fox** RPI, **Steve Kempler** NASA/GSFC and **Manil Maskey** UAH

MSFC/UAH: Patrick Gatlin, Xiang Li, Amanda Weigel, JJ Miller, Kaylin Bugbee, Ajinkya Kulkarni

GSFC: Chris Lynnes, Suhung Shen, Chung-Lin Shie, Maksym Petrenko

RPI: Stefan Zednik, Anirudh Prabhu



Outline

1. Project Overview
2. Data Curation Service
3. Rules Engine
4. Image Retrieval Service
5. Summary

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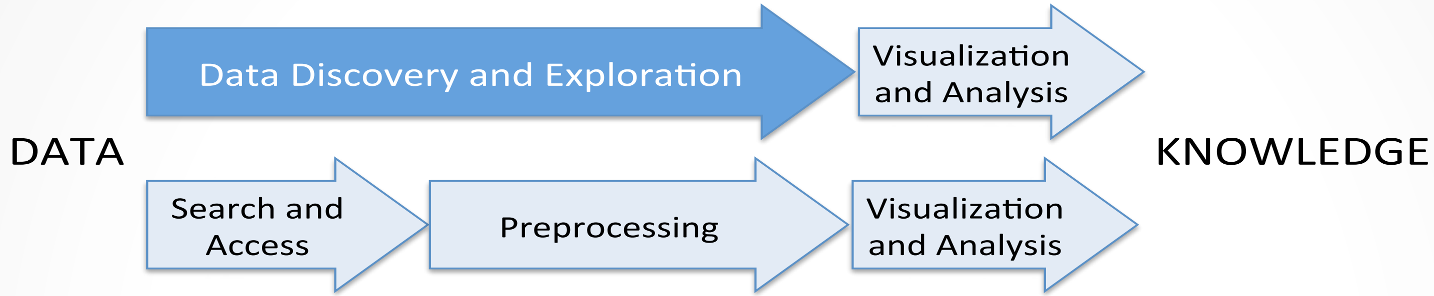
Part 1: Project Overview

Motivation



- Data preparation steps are **cumbersome** and **time consuming**
  - Covers discovery, access and preprocessing
- Limitations of current Data/Information Systems
  - **Boolean search** on data based on instrument or geophysical or other **keywords**
  - Underlying **assumption** that users have sufficient knowledge of the **domain vocabulary**
  - **Lack support** for those **unfamiliar** with the domain vocabulary or the **breadth of relevant data** available

Earth Science Metadata: Dark Resources

- *Dark resources* - information resources that organizations collect, process, and store for regular business or operational activities but fail to utilize for ***other*** purposes
  - Challenge is to recognize, identify and effectively utilize these dark data stores
- Metadata catalogs contain dark resources consisting of structured information, free form descriptions of data and browse images.
  - EOS Clearing House (ECHO) holds >6000data collections, 127 million records for individual files and 67 million browse images.

Premise: Metadata catalogs can be utilized *beyond their original design intent* to provide *new data discovery and exploration pathways* to support science and education communities.

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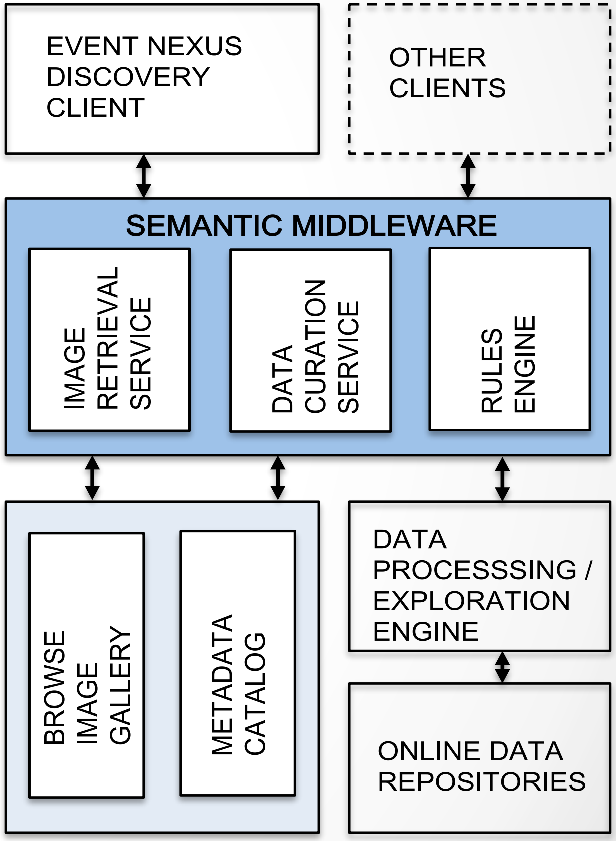
Goals

- Design a Semantic Middleware Layer (SML) to exploit these metadata resources
  - provide novel ***data discovery and exploration*** capabilities that significantly reduce data preparation time.
  - utilize a varied set of semantic web, information retrieval and image mining technologies.
- Design SML as a Service Oriented Architecture (SOA) to allow individual components to be used by existing systems



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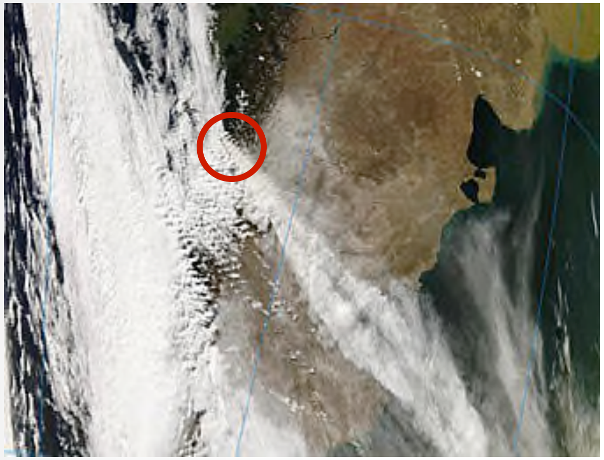
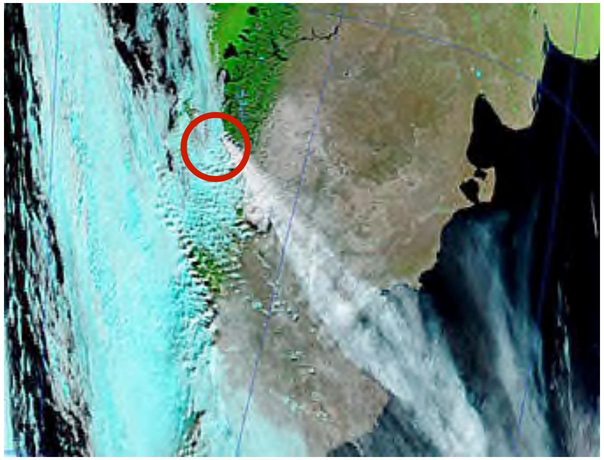
Science Use Cases

- Dust storms, Volcanic Eruptions, Tropical Storms/ Hurricanes
- *Volcanic Eruptions*:
  - Emit a variety of gases as well as volcanic ash, which are in turn affected by atmospheric conditions such as winds.
  - Role of Components
    - **Image Retrieval Service** is used to **find volcanic ash events** in browse imagery
    - **Data Curation Service** suggests the **relevant datasets** to support event analysis
    - **Rules Engine** invokes a **Giovanni processing workflow** to assemble and compare the wind, aerosol and SO2 data for the event

Find Events: Browse Images



Band 1-4-3 (true color)



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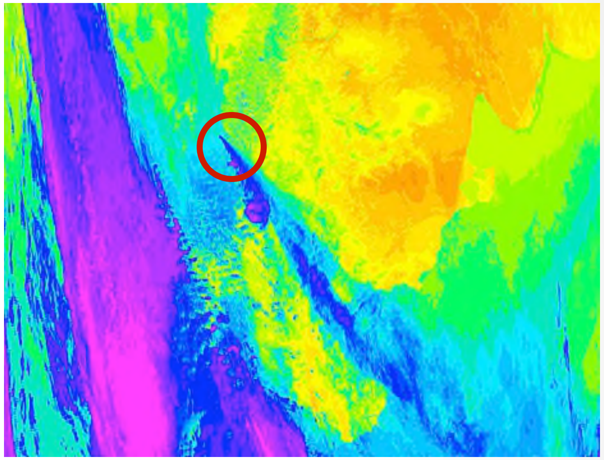

LST

Example: MODIS-Aqua 2008-05-03 18:45 UTC

Chaitén Volcano Eruption
Eruption Time period: May 2 – Nov 2008
Location: Andes region, Chile (-42.832778, -72.645833)

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Suggest Relevant Data

Total SO_2 mass:
e.g. **Chaitén** is 10 (kt) =(kilotons) , (1kt= 1000 metric tons)
ftp://measures.gsfc.nasa.gov/data/s4pa/SO2/MSVOLSO2L4.1/MSVOLSO2L4_v01-00-2014m1002.txt

Daily SO2:
OMI/Aura Sulphur Dioxide (SO2) Total Column Daily L2 Global 0.125 deg
http://disc.sci.gsfc.nasa.gov/datacollection/OMSO2G_V003.html

Calibrated Radiances:
MODIS/Aqua Calibrated Radiances 5-Min L1B Swath 1km
http://dx.doi.org/10.5067/modis/myd021km.006

Aerosol Optical Thickness:
MODIS/Aqua Aerosol 5-Min L2 Swath 10km
http://modis-atmos.gsfc.nasa.gov/MOD04_L2/
SeaWiFS Deep Blue Aerosol Optical Depth and Angstrom Exponent Level 2 Data 13.5km
http://disc.gsfc.nasa.gov/datacollection/SWDB_L2_V004.shtml

IR Brightness Temperature:
NCEP/CPC 4-km Global (60 deg N - 60 deg S) Merged IR Brightness Temperature Dataset

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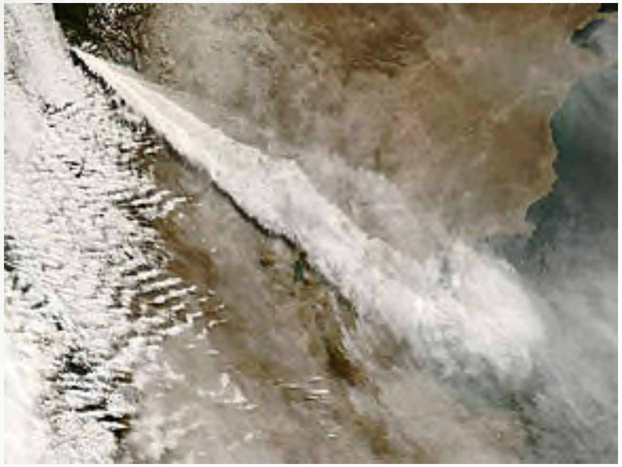
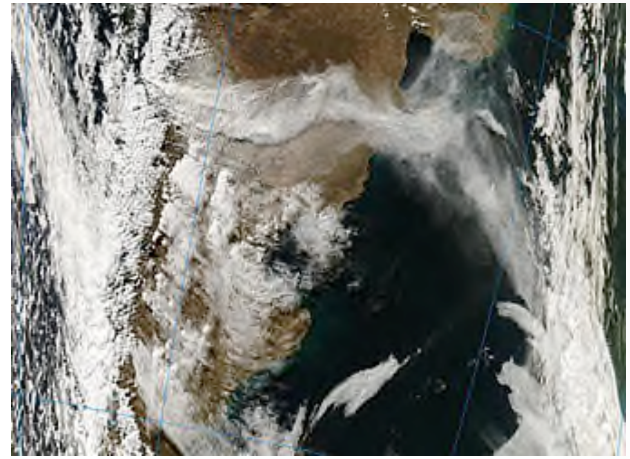
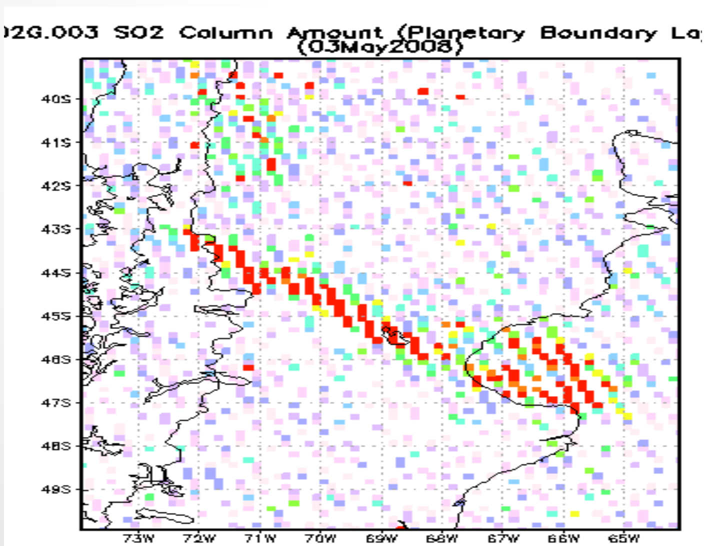
Generate Giovanni SO2 Plots

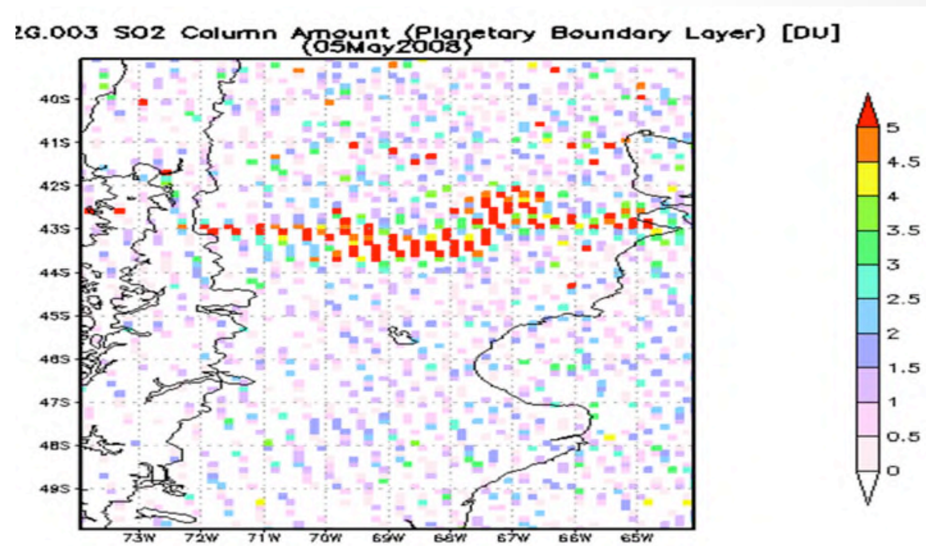
MODIS-Aqua 2008-05-03 18:45 UTC



MODIS-Aqua 2008-05-05 18:30 UTC



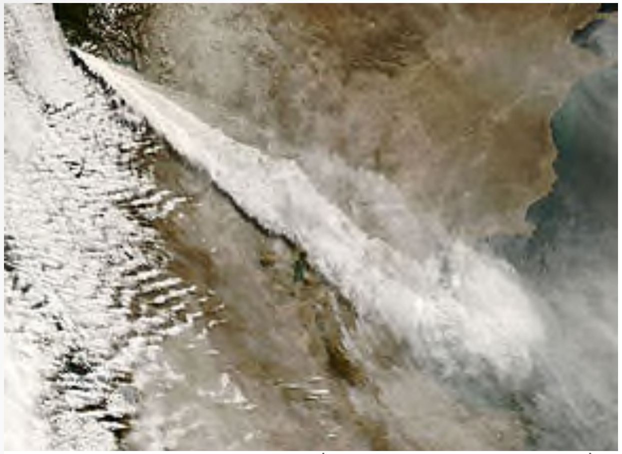


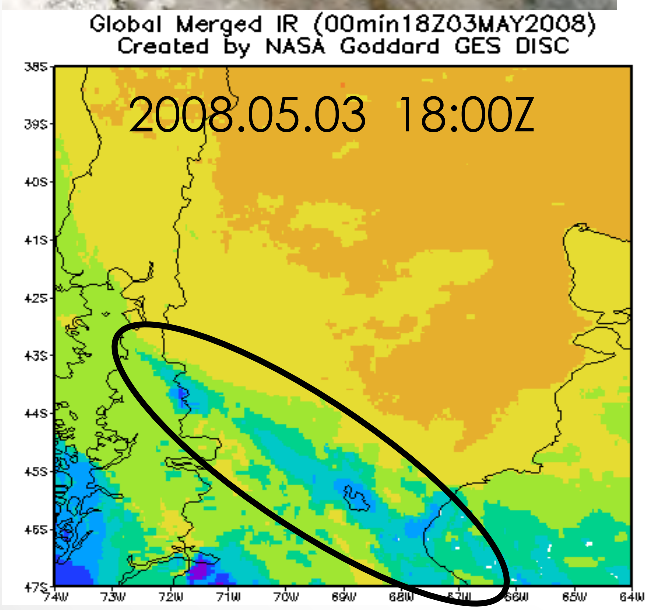


http://gdata2.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance_id=omil2g

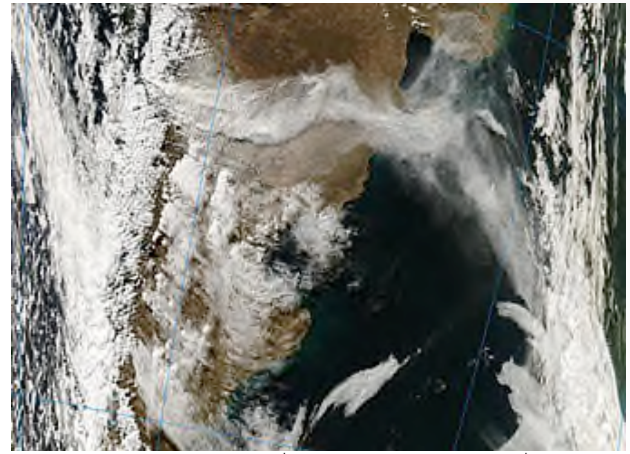
Generate Giovanni Infrared Data Plot

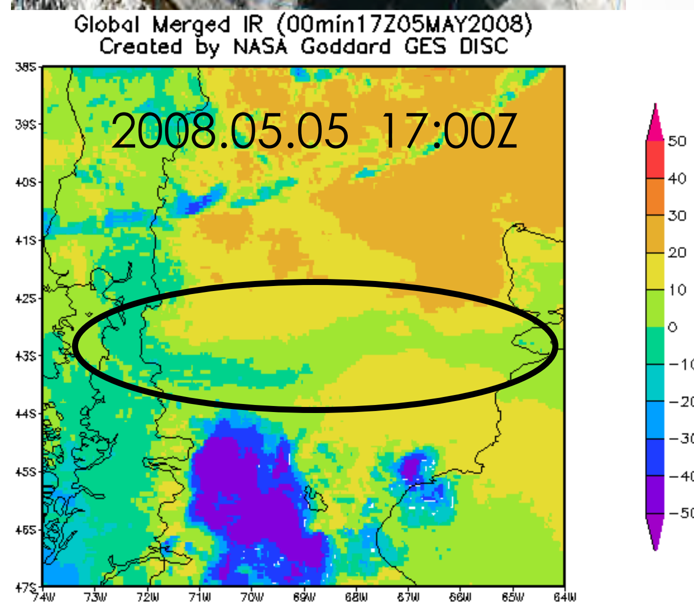
MODIS-Aqua 2008-05-03 18:45 UTC





MODIS-Aqua 2008-05-05 18:30 UTC

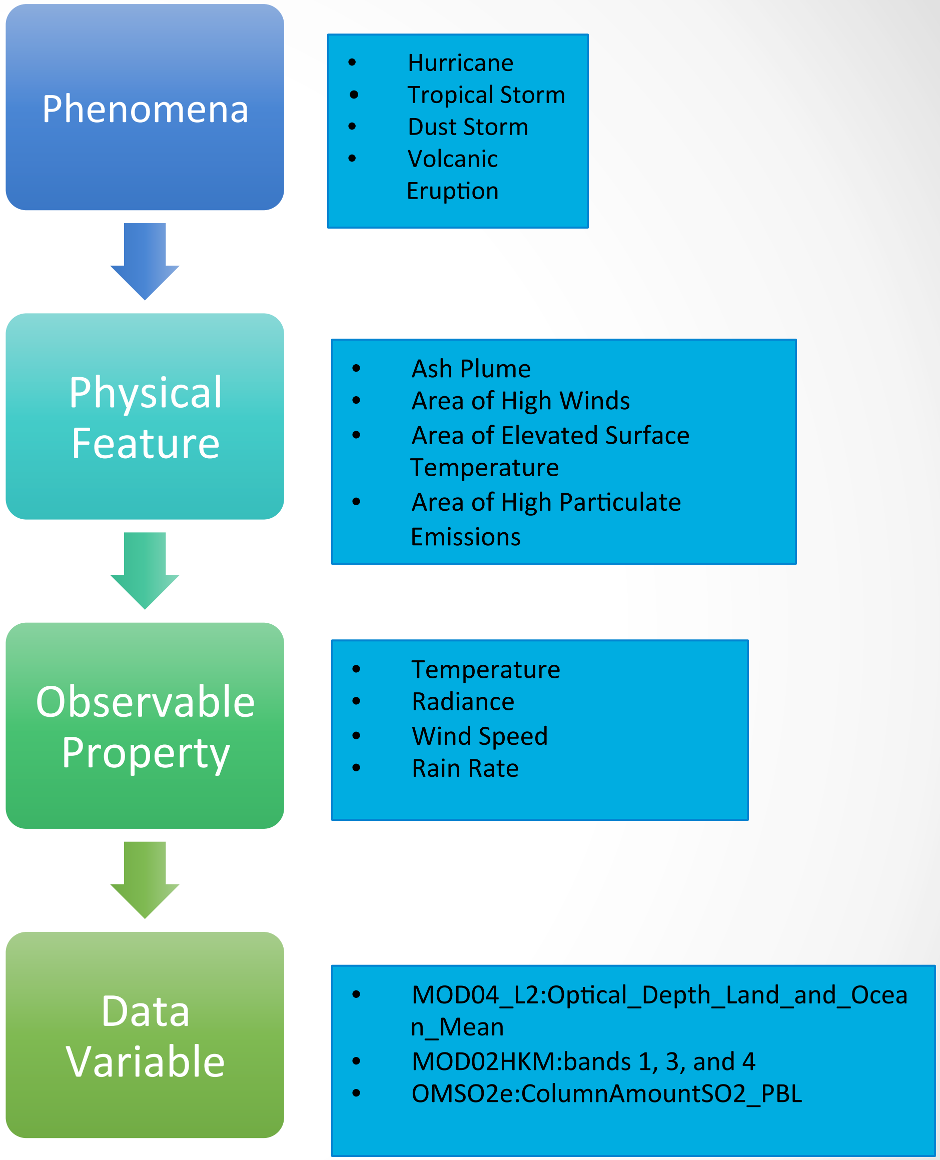




http://disc.sci.gsfc.nasa.gov/daac-bin/hurricane_data_analysis_tool.pl

Conceptual Model

- Phenomena
  - Event type
- Physical Feature
  - Manifestation / Driver of phenomena
  - Has space/time extent
  - Can precede or linger after what is generally thought of as the phenomena event
- Observable Property
  - Characteristic/property of physical feature
- Data Variable
  - Measurement/estimation of observable feature



Part 2: Data Curation Algorithm for Phenomena

Initial Results

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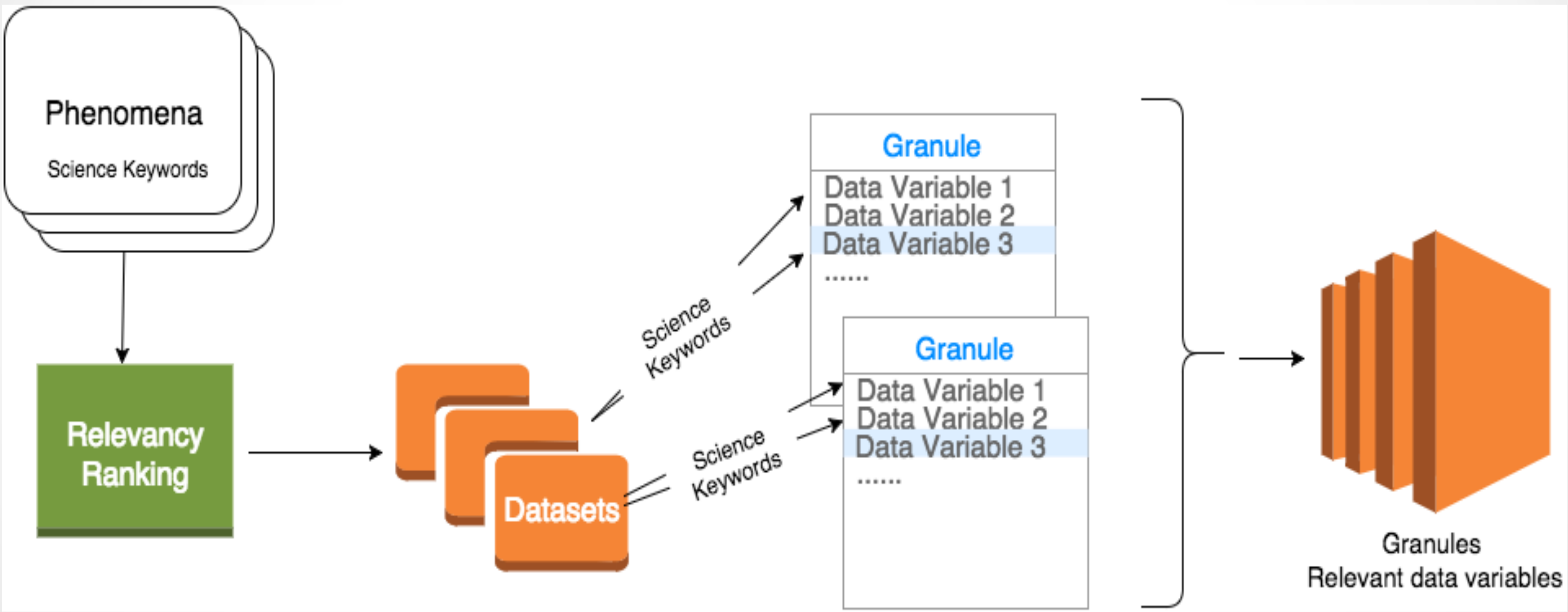
Objectives

- Design a data curation (relevancy ranking) algorithm for a set of **phenomena**
- Provide the data curation algorithm as a stand alone service

- Envisioned Use:
  - Given a phenomenon type (Ex: Hurricane), DCS returns a list of relevant data sets (variables)
    - <data of data sets> = DCS(Phenomenon Type)
  - For a specific phenomenon instance (event: Hurricane Katrina), these curated datasets can then be filtered based on space/time to get actual granules

Overview

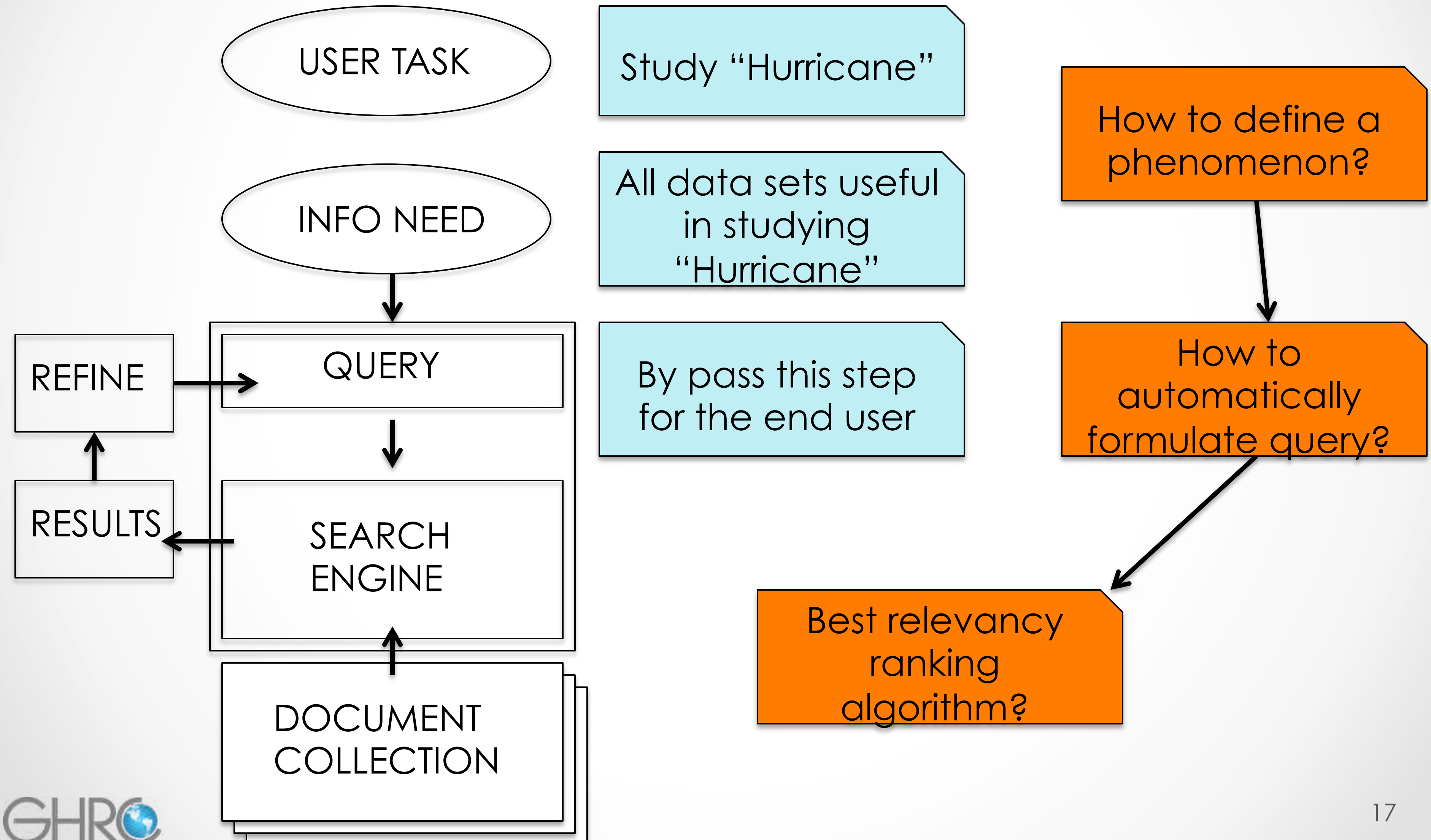


Phenomena
Science Keywords
Relevancy Ranking
Datasets
Science Keywords
Science Keywords
Granule
Data Variable 1
Data Variable 2
Data Variable 3
....
Granule
Data Variable 1
Data Variable 2
Data Variable 3
....
Granules
Relevant data variables

Data Curation Algorithm Approaches

- Text mining
  - Pros: Don't need to explicitly define the phenomena
  - Cons: Dependent of the truth set; Catalog is dynamic and new data may never get classified
- Ontology Based
  - Pros: Best precision and recall
  - Cons: Labor intensive to build an explicit model and map to instances
- Information Retrieval
  - Boolean (Faceted) Search
    - Pros: Simple to implement
    - Cons: Phenomena can be complex; User may not know all the right keywords
  - Relevancy Ranking Algorithm
    - Pros: List most relevant data first
    - Cons: ***Requires a custom algorithm***

Data Search for Earth Science Phenomena



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Relevancy Ranking

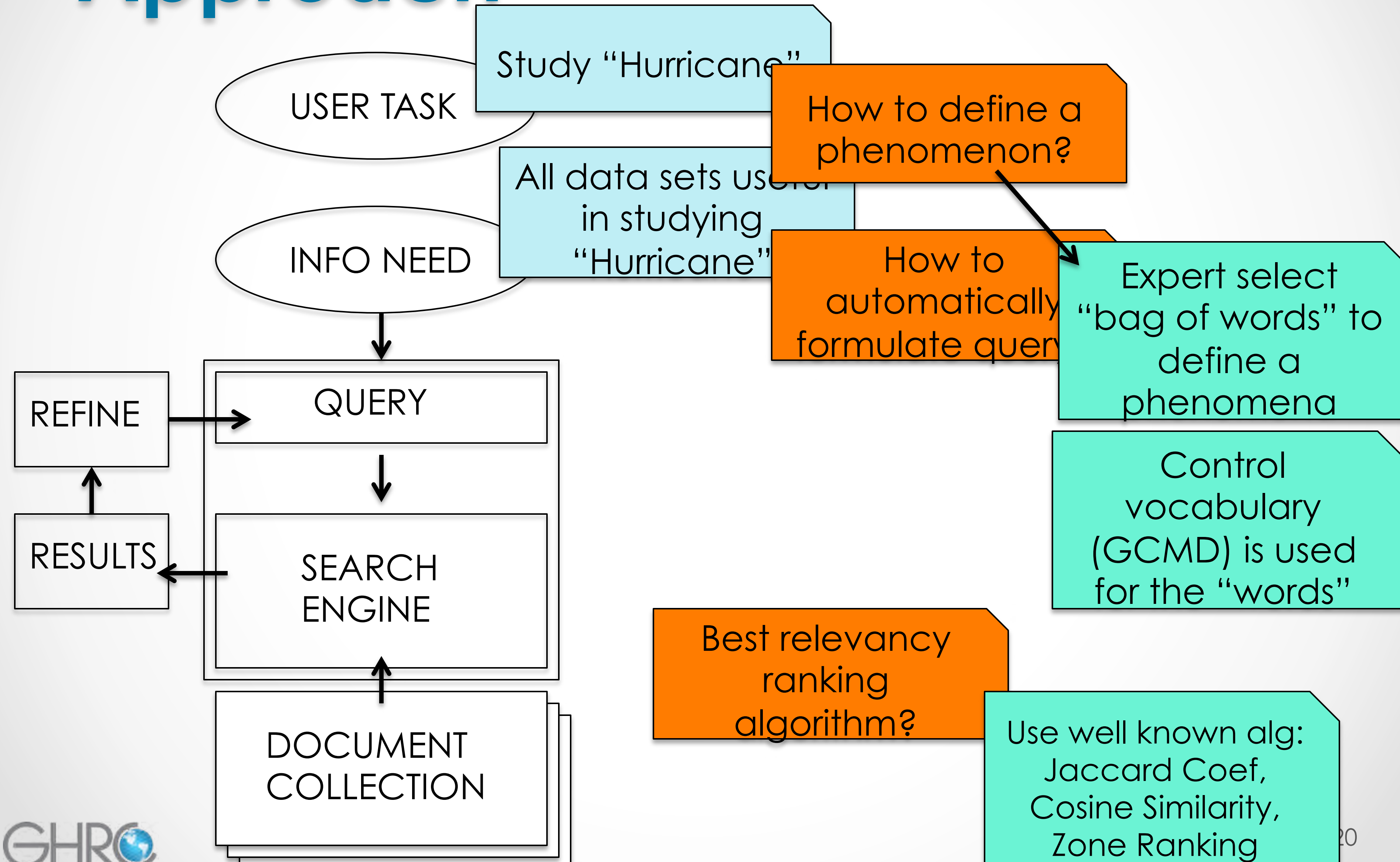
- Search: Curation problem

- Data curation: **Relevancy ranking** service for a set of Earth science **phenomena**

Relevancy Ranking: Initial Exploratory Experiments

- Approaches tested:
  - O-Rank (Top down approach)
  - Wikipedia Terms
  - Manual Terms Experiment
  - Latent Semantic Index – Dual Set terms
  - Metadata based Ranking
- Key Takeaways:
  - Best results: three approaches where terms describing the phenomenon manually constructed after exploring metadata records
  - Both ontology and automated term construction (Wiki) approaches don't map well to metadata terms/descriptions

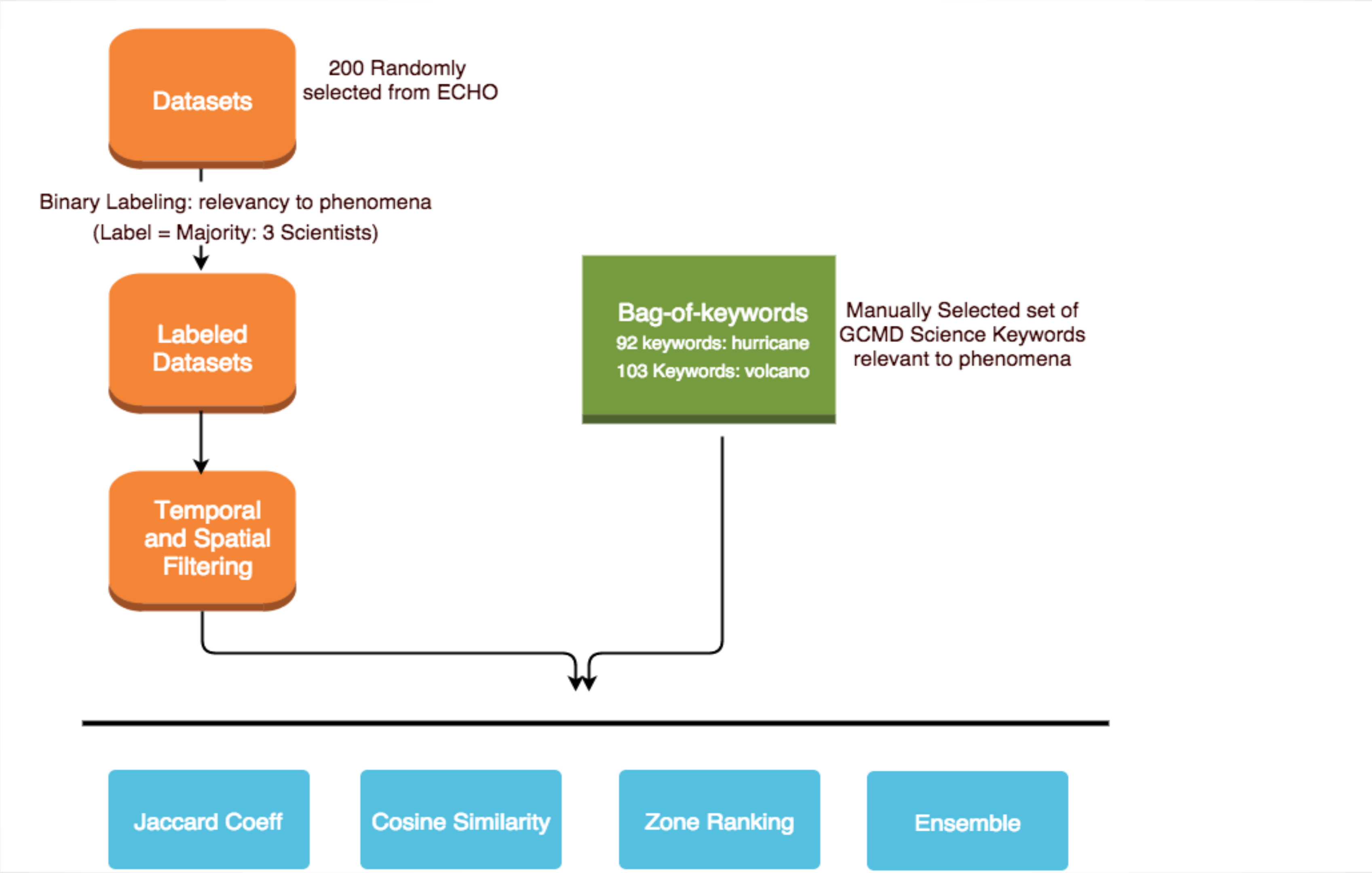
Follow-on Experiments: Approach



Assumptions/Observations

- Metadata quality
  - Richness
  - Vocabulary
  - Tags
- Earth Science Phenomena *can be* defined using a bag of keywords

Experiment Setup



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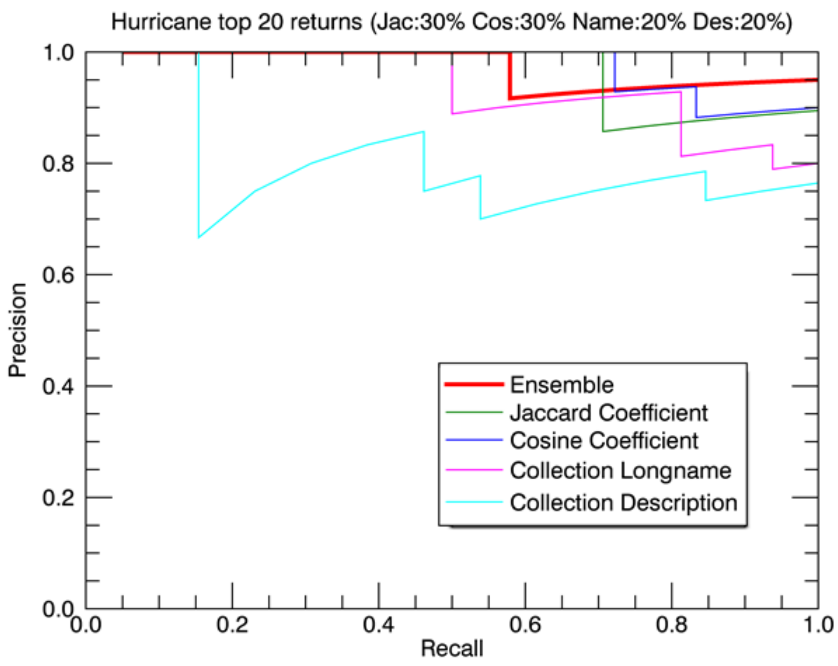
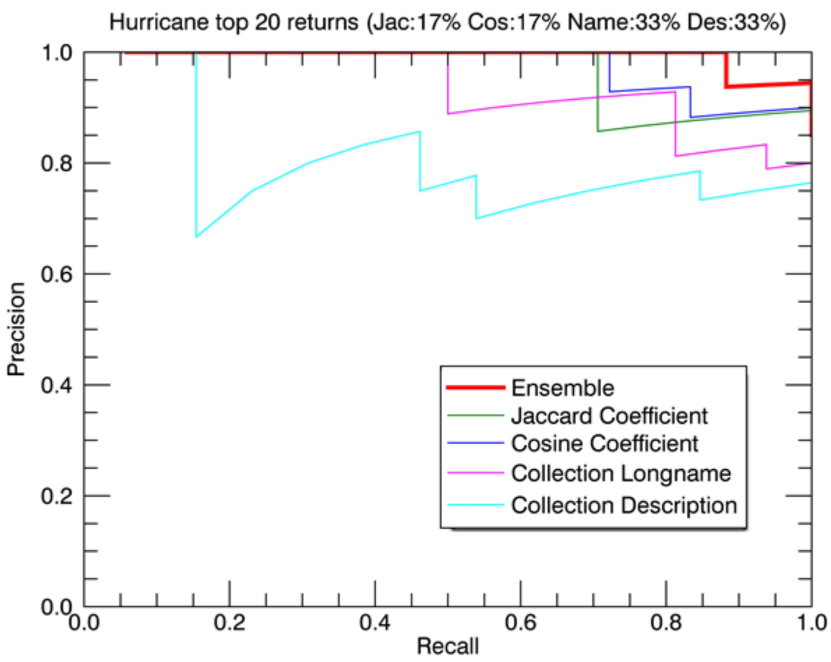
Top 20 returns (Hurricane)

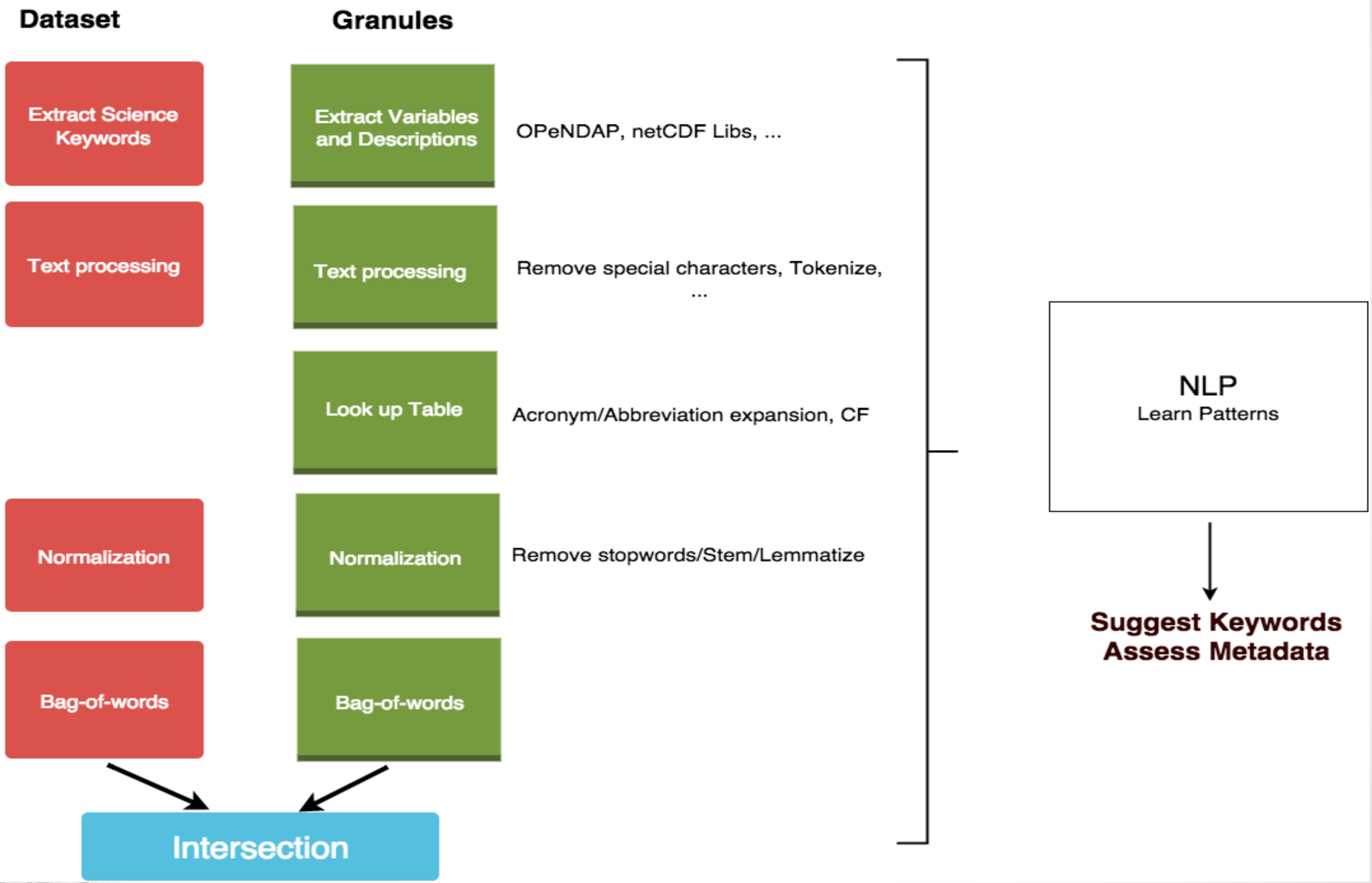




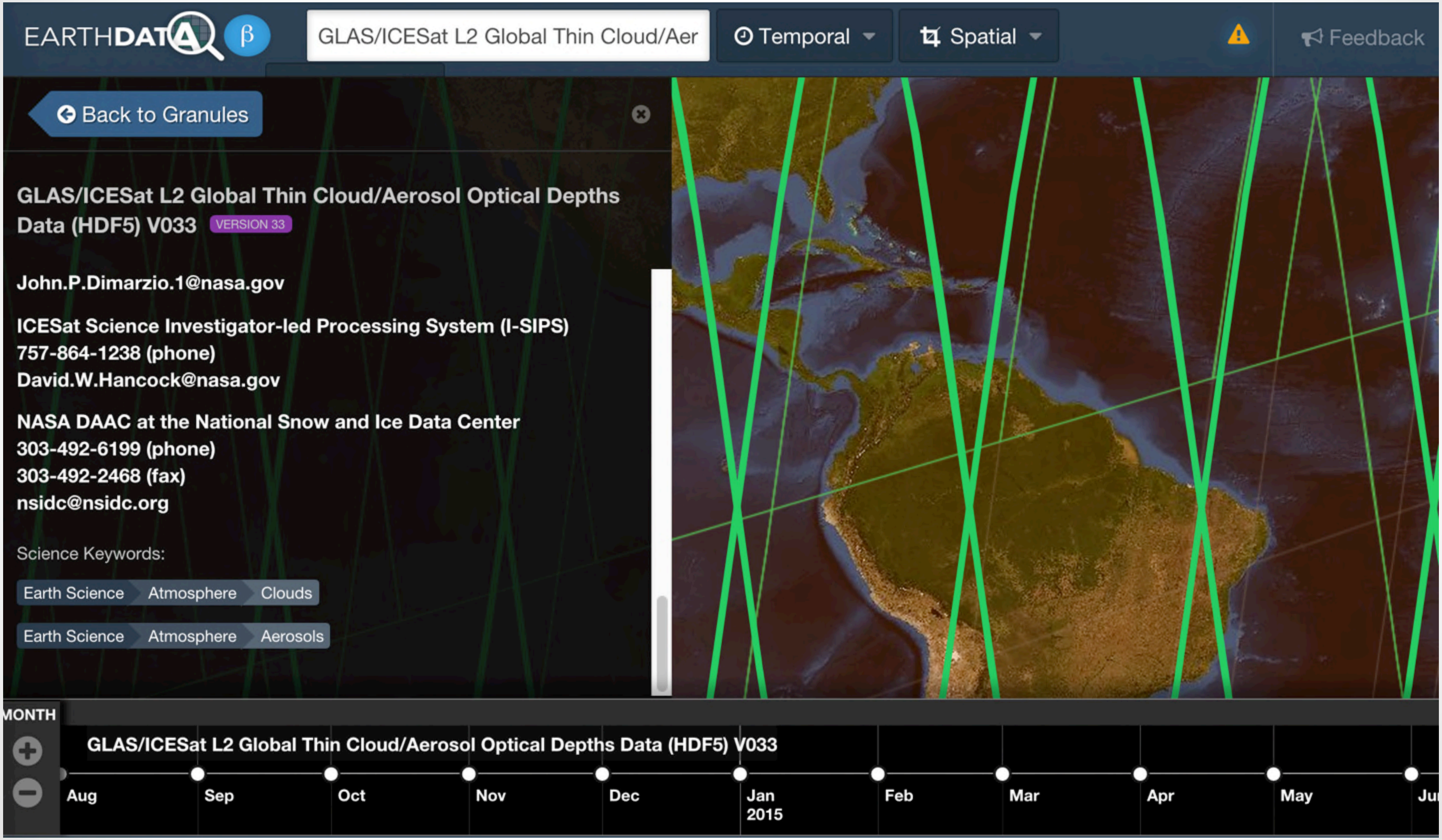
Next: Find relevant data fields

- Dataset is relevant
  - now what?
  - how do I use the granules for the dataset?
- Need actual data variable name
  - for example: Giovanni uses these fields for visualization
- What we know
  - relevant science keywords (GCMD) – Experts
  - granule data fields and metadata – Auto extract*
- How do we map?
  - manually? May work for few datasets only
    - Hundreds of data variables per granule
  - start with GCMD to CF Standard name
  - most don't follow CF Standard names

Approach


Dataset
Granules
Extract Science Keywords
Extract Variables and Descriptions
OPeNDAP, netCDF Libs, ...
Text processing
Text processing
Remove special characters, Tokenize, ...
Look up Table
Acronym/Abbreviation expansion, CF
Normalization
Normalization
Remove stopwords/Stem/Lemmatize
Bag-of-words
Bag-of-words
Intersection
NLP
Learn Patterns
Suggest Keywords
Assess Metadata

Example: GLAS/ICESat L2 Global Thin Cloud/Aerosol Optical Depths Data (HDF5) V033 – Dataset Metadata



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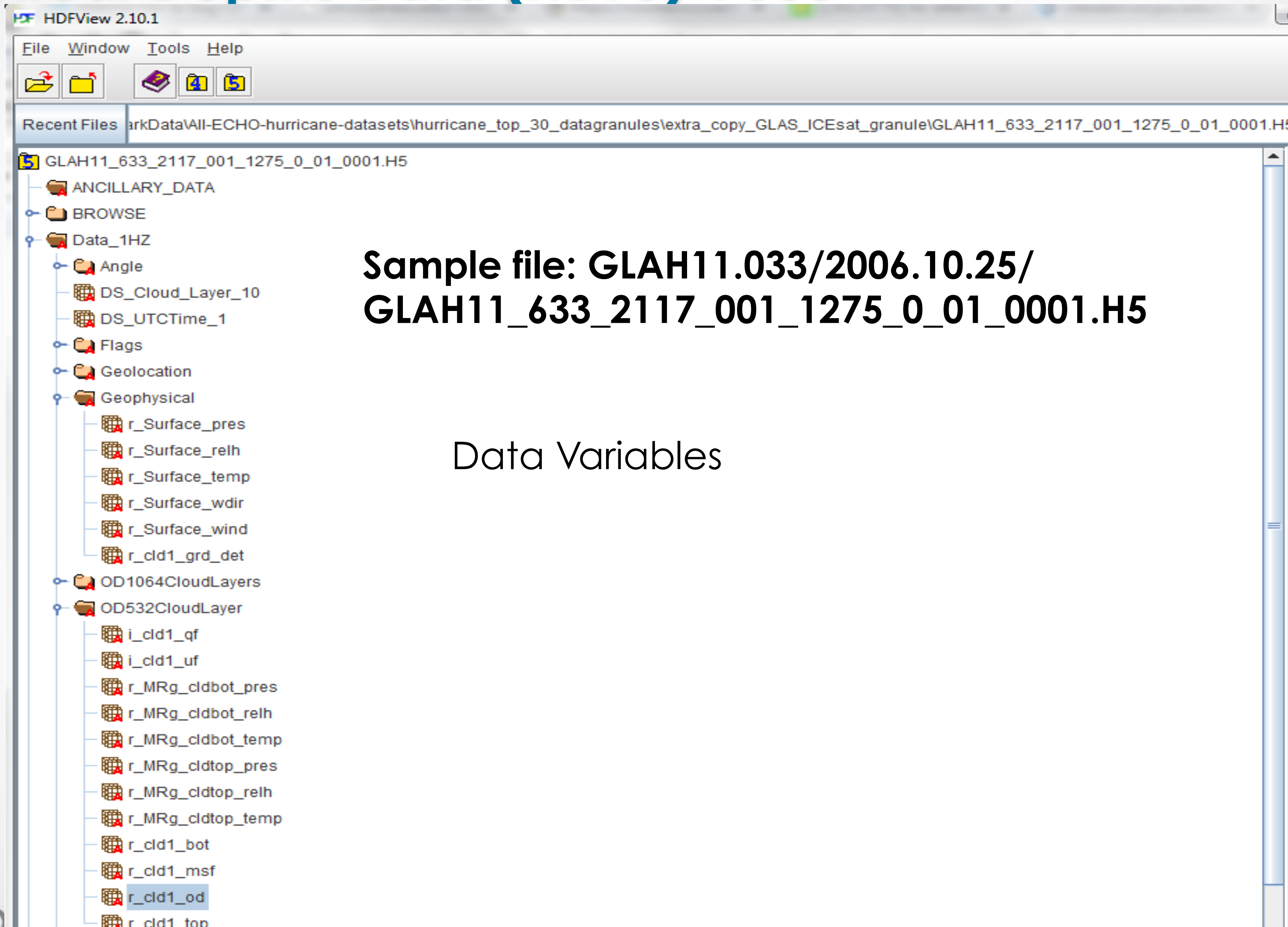
Example: GLAS/ICESat L2 Global Thin Cloud/Aerosol Optical Depths Data (HDF5) V033



Sample file: GLAH11.033/2006.10.25/ GLAH11_633_2117_001_1275_0_01_0001.H5

Data Variables

Example: GLASICESat L2 Global Thin Cloud Aerosol Optical Depths Data (HDF5) V033

Science keyword to variable mapping

- r_Surface_relh | Surface Relative Humidity
  - No match
- r_Surface_temp | Surface Temperature
  - No match
- r_Surface_wind | Surface Wind Speed
  - No match
- r_cld1_od | Cloud Optical Depth at 532 nm
  - Score=3 keyword: ATMOSPHERE->CLOUDS->CLOUD OPTICAL DEPTH/THICKNESS
  - Score=2 keyword: ATMOSPHERE->AEROSOLS->AEROSOL OPTICAL DEPTH/THICKNESS

Variable to keyword mapping

- ATMOSPHERE->CLOUDS->CLOUD OPTICAL DEPTH/THICKNESS
  - Score=3 name: r_cld_ir_OD | Cloud Optical Depth at 1064 nm
  - score=3 name:i_cld1_qf | Cloud optical depth flag for 532 nm
  - Score=3 name:i_cld1_uf | Cloud optical depth flag for 532 nm
  - Score=3 name:r_cld1_od | Cloud Optical Depth at 532 nm
  - more with low scores

This approach can be used to assess metadata quality and also suggest keyword annotation!!

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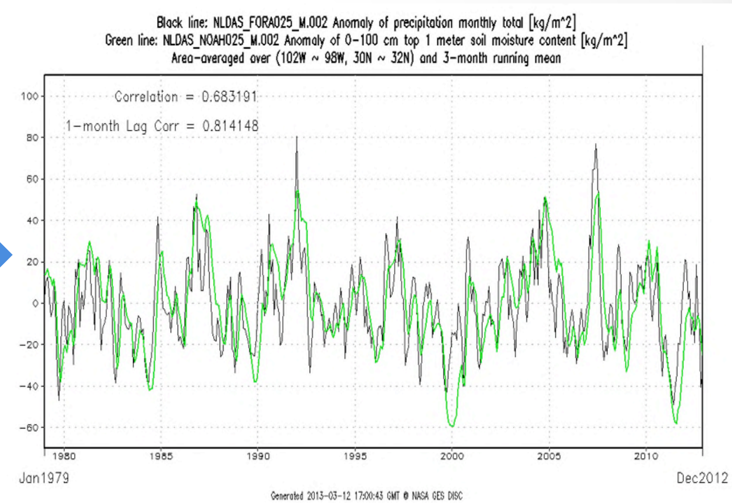
Part 3: Rules Engine

What Settings should I use to visualize this event?



Data Variable?

Dataset?

Visualization Type?

Goal: Automate data preprocessing and exploratory analysis and visualization tasks

Images from : http://globe-views.com/dcim/dreams/volcano/volcano-03.jpg , http://grecaira.users37.interdns.co.uk/essay/images/confused.png , http://disc.sci.gsfc.nasa.gov/datareleases/images/nldas_monthly_climatology_figure_9.gif

Strategy

- Service to generate and rank candidate workflow configurations
- Use rules to make assertions about compatibility based on multiple factors
  - does this data variable make sense for this feature?
  - does this visualization type make sense for this feature?
  - does the temporal / spatial resolution of this dataset make sense for this feature?
- Each compatibility assertion type is assigned weights.
  - ex: Strong = 5, Some = 3, Slight = 1, Indifferent = 0, Negative = -1.
- Based on the aggregated compatibility assertions, we calculate the score for each visualization candidate.

Phenomena Feature Characteristic Mappings

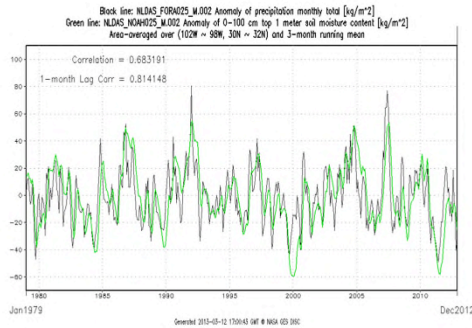
Phenomena	East-West Movement	North-South Movement	Temporal Evolution	Spatial Extent of Event	Year-to-Year Variability	May Impact Seasonal Variation	Variation with Atmospheric Height	Global Phenomena	Detection of Events
Volcano - Ash Plume	Indifferent	Indifferent	Strong	Slight	Strong	Strong	Strong	Strong	Strong
Flood	Some	Some	Strong	Some	Some	Strong	Some	Slight	Some
Dust Storm	Strong	Strong	Strong	Strong	Indifferent	Indifferent	Strong	Indifferent	Some

Service to Characteristic Mappings

Service	Visualization	East-West Movement	North-South Movement	Temporal Evolution	Spatial Extent of Event	Year-to-Year Variability	Seasonal Variation	Variation with Atmospheric Height	Global Phenomena	Detection of Events
Time-averaged Map	Color-Slice Map				✓					
Area-averaged Time Series	Time Series			✓						✓
User-defined Climatology	Color-Slice Map						✓			
Vertical Profile	Line Plot							✓		
Seasonal Time Series	Time Series					✓				
Zonal Means	Line Plot								✓	
Hovmoller (Longitude)	Color-Slice Grid	✓								
Hovmoller (Latitude)	Color-Slice Grid		✓							

Compute Compatibility

+



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Phenomena: Volcano - Ash Plume

Temporal Evolution	Detection of Events
Strong	**Strong**

Service - Area Averaged Time Series

Area Averaged Time Series : bestFor →	Temporal evolution; Detection of events

STRONG COMPATIBILITY x2

Images from :http://i.dailymail.co.uk/i/pix/2010/05/18/article-1279221-09A0CCC4000005DC-385_634x433.jpg,http://disc.sci.gsfc.nasa.gov/datareleases/images/nldas_monthly_climatology_figure_9.gif,http://www.clipartbest.com/cliparts/biy/bAX/biybAXGiL.png

Next Steps

- Generate rules for compatibility assertions based on
  - data variables
  - temporal / spatial resolution
  - dataset processing
- Explore additional strategies for making compatibility assertions

Part 4: Image Retrieval

Initial Results

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Image Retrieval

- Goal: given an image of Earth science phenomenon retrieve similar images
- Challenge: “semantic gap”
  - low-level image pixels and high-level semantic concepts perceived by human

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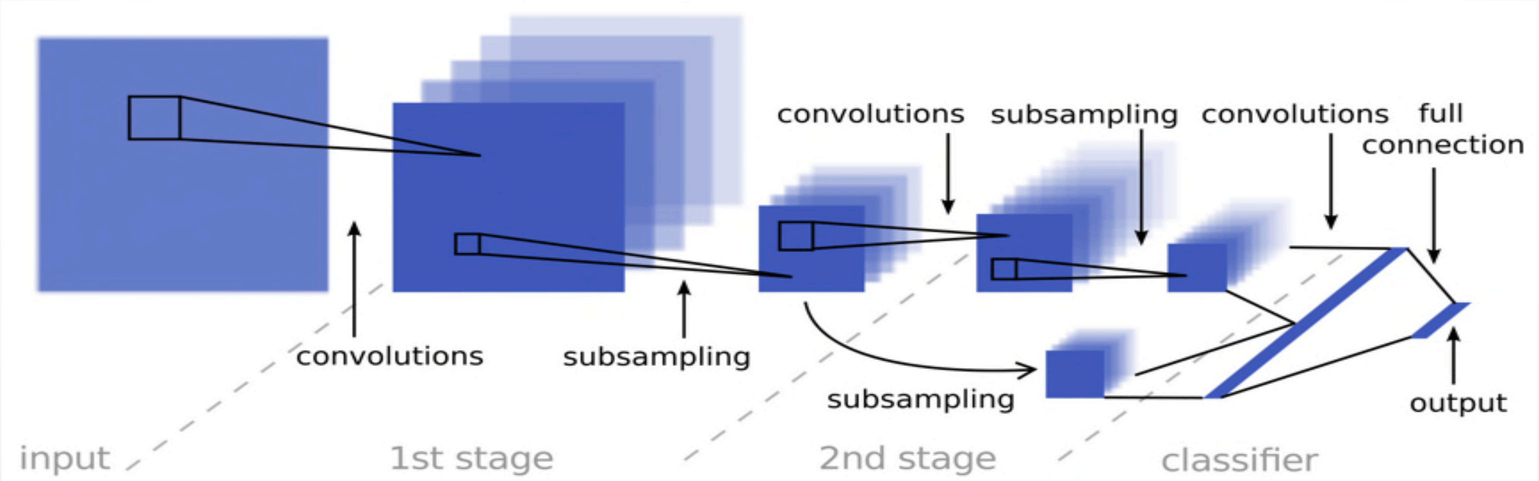
Image retrieval approaches

- Tradition approaches
  - Image features: Color, Texture, Edge histogram…
  - “Shallow” architecture
  - User defines the feature
  - Preliminary experiments

- State of the Art approach
  - Generic
  - No need for domain expert

Deep Learning

- Mimics the human brain that is organized in a deep architecture
- Processes information through multiple stages of transformation and representation
- Learns complex functions that directly map pixels to the output, without relying on human-crafted features



Convolution neural network

Source: Google Research, CVPR 2014

Experiment Setup

- NASA rapid response MODIS imageries
- 600 imageries
- 3 phenomena – Hurricane, Dust, Smoke/ Haze
- Train half images with Convolutional Neural Network
- Test

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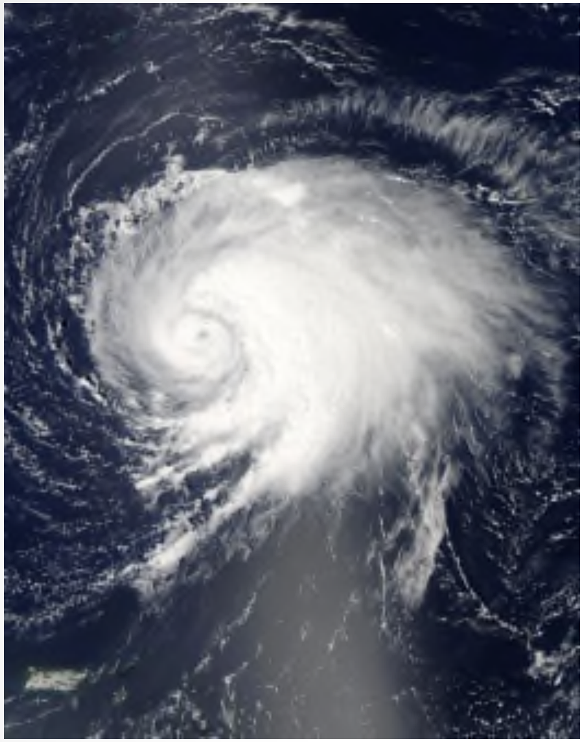
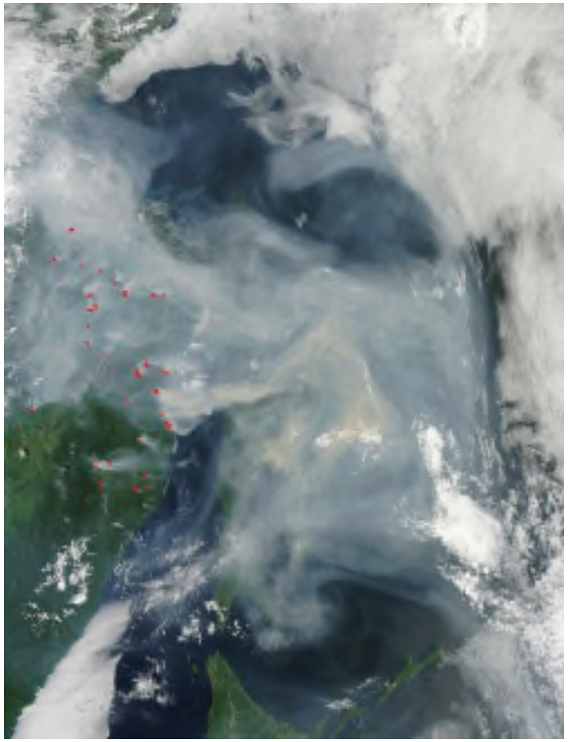
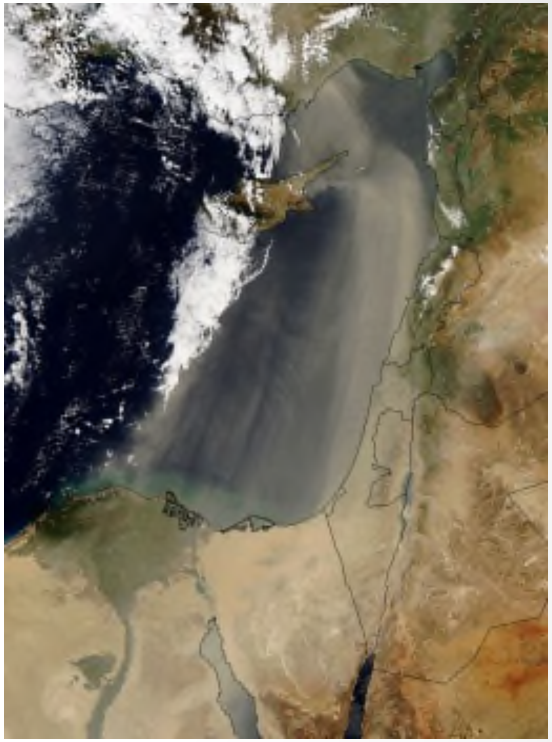
Sample rapid response images



Hurricane



Smoke



Dust

4 layers

- Used number of filters in each layer = 100, 200, 400, 800
- Convolved and Pooled on every layer
- Overall accuracy ~ = as that of 5 layers (slightly better than 6 layers)

Error Matrix

4 layers, learning rate = 0.003

True\Pred	Others	dust	Haze/smoke	Hurricane
Others	173	20	76	7
dust	29	128	23	0
Haze/Smoke	79	3	207	7
Hurricane	30	2	3	163

Accuracy Numbers

Producers Accuracy

• Other:	173/311	= 55.6%
• Dust:	128/153	= 83.7%
• Smoke:	207/309	= 67%
• Hurricane:	163/177	= 92.1%

Users Accuracy

• Other:	173/276	= 62.7%
• Dust:	128/180	= 71.1%
• Smoke:	207/296	= 69.9%
• Hurricane:	163/198	= 82.3%

Overall accuracy ~ 70.6%

Summary

- Build three specific semantic middleware core components
  - *Image retrieval service* - uses browse imagery to enable discovery of possible new case studies and also presents exploratory analytics.
  - *Data curation service* - uses metadata and textual descriptions to find relevant data sets and granules needed to support the analysis of a phenomena or a topic.
  - *Semantic rules engine* - automates data preprocessing and exploratory analysis and visualization tasks.

Explore pathways to infuse these components into existing NASA information and data system